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Image Enhancement Based on Edge Profile Acutance

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Abstract

The sharpness of an image is related to the higher-frequency content of the image and to the edge information in the image. Increasing values of derivative measures across edges should relate to sharper and more clearly perceivable image details. The mean-squared gradient is a reliable measure of edge sharpness, and has been used in the definition of the "acutance" of an edge or region of interest (ROI). Acutance could also serve as a local measure of image quality or the perceptibility of a region or feature of interest in an image. We propose a new method of computing image edge profile acutance based on the mean-squared gradient along the normals to the boundary of an ROI Image enhancement techniques are then proposed based on the idea of increasing the acutance of an ROI. For this purpose, one-dimensional operators are applied to sets of pixels along the normals at each boundary pixel of an ROI

The acutance algorithm has been tested on different test images, and the resulting values have been found to relate well to the perceived sharpness of the image. The enhancement method has been tested with different blurred test images, and has been found to increase their sharpness as well as the objective measure of acutance.

1. Introduction

The process of capturing images of objects and scenes usually involves some degradation and loss of quality. The field of digital image processing provides a number of techniques to improve the quality of digital images by modifying image characteristics such as sharpness, contrast, dynamic range, and frequency content. However, judging the degree of improvement in perceptual quality provided by an operation is a rather difficult task. The need for objective correlates of the inherently subjective properties of image sharpness, crispness, quality, and perceptibility of details has been recognized for a long time (see Rangayyan and Elkadiki[1] for a review).

The sharpness of an image is related to the higher spatial frequency content of the image and to the edge information in the image. Increased values of the derivatives of edges contribute to the higher spatial frequencies in the image and make the image appear sharper.

Higgins and Jones[2] discussed evaluation of sharpness of photographic images, with particular attention to the importance of gradients. They found that the maximum gradient or average gradient measures along knife-edge spread functions (KESFs) failed to correlate with sharpness, but that the mean-squared gradient across the KESFs, or acutance, indicated excellent correlation with subjective judgement of sharpness.

Wolfe and Eisen[3] stated that sharpness of an image is a subjective concept and is an impression made on the mind of an observer when viewing a picture. They observed that resolving power and sharpness do not have any psychophysical relationship. They also found that the maximum and average gradients do not correlate well with the sharpness of the image. They stated that the variation of density across an edge is an obvious physical measurement to be investigated to obtain an objective correlate of sharpness.

Crane[4] discussed the need for objective correlates of the subjective property of image sharpness or crispness; he remarked that resolving power is misleading, that the averaged squared gradient of edge profiles is dependable but cannot include the effects of all components in a photographic system (camera to viewer), and that spread functions and modulation transfer functions (MTFs) are not easy to comprehend, compare, or tabulate. He proposed a single numerical rating based on the areas under the MTF curves of all the systems in the chain from the camera to the viewer called "system modulation transfer or SMT acutance" (SMTA). Later, Gendron[5] proposed a "cascaded modulation transfer or CMT" measure of acutance (CMTA) to rectify some deficiencies in SMTA. CMTA was used by Kriss to compare sharpness of imaging systems[6].

Perrin[7] took the mean-squared gradient measurement over many sections of the KESF, normalized the measured values with respect to the density difference across the knife edge, and called it acutance.

Higgins[8] discussed various methods for analyzing photographic systems, including the effects of nonlinearity, line spread functions (LSFs), MTFs, granularity, and sharpness. He also discussed quality criteria as related to objective or subjective tone reproduction, sharpness, and graininess, and recommended that MTF-based acutance measures are good when no graininess is present; signal-to-noise ratio (SNR) based measures were found to be better otherwise[9].

The acutance measure proposed by Higgins and Jones[2] is given by the formula

$$A = \frac{1}{f(b) - f(a)} \int_a^b \left(\frac{df}{dx} \right)^2 dx, \tag{1}$$

where $f(x)$ is a section across the edge image profile (or KESF), and a and b are the edge start and end points, respectively. $(b - a)$ is related to the resolution of the edge, and $(f(b) - f(a))$ is related to the contrast of the edge (see also Hall[10]).

The concept of edge sharpness of an image is particularly important in visual perception of an image. Grossberg[11] stated that an important early stage of human vision involves the calculation of an edge map. He also proposed that perception of brightness is controlled by a diffusion process in which the perceived contrast of the edges acts as an insulation strength that partially blocks the diffusion. Attenave[12] stated that human beings are able to recognize objects starting from a very crude outline, and that edge detection may be the most important method of feature extraction in low-level vision.

The psychophysical importance of edge sharpness reflects itself in recent adaptive image contrast enhancement techniques. Some of the current adaptive contrast enhancement techniques have been developed with a view to take explicit account of local image structures (Morrow et al.[13]). Perona and Malik[14], working in the context of edge detection and the theory of scale-space anisotropic diffusion, developed a way of producing truly variable contextual regions for contrast enhancement in a manner very much like the description of the human visual system given by Grossberg[11]. Beghdadi and Le Negrate[15] used a modified contrast definition based on the detection of edges within contextual regions. Cromartie and Pizer[16] discussed the importance of edges in contrast perception and outlined the development of two adaptive contrast enhancement methods which take into account edge information in the image.

The concept of image sharpness or acutance has also the potential to serve as a local measure of image quality or the perceptibility of a region or feature of interest. This has immense application in various fields, such as medical imaging, where one may obtain an array of images of the same patient (or phantom) using different imaging systems. The radiologist or medical physicist would be interested in evaluating which system or set of parameters provides the image where a specific object, such as a tumor, can be perceived the best. Consequently, intensive research has been directed towards finding a measure of sharpness of an object or region of interest (ROI); please refer to Rangayyan and Elkadiki[1] and El-Faramawy et al.[17] for detailed reviews on this topic.

Many methods are available to increase image sharpness. They may be classified into two broad categories: fixed neighborhood methods, such as subtracting Laplacian and unsharp masking (see Gonzalez and Woods[18]), and adaptive image sharpening methods. Some of the adaptive image sharpening and edge enhancement methods are reviewed below.

Marr[19], Marr and Hildreth[20], and Hildreth[21] relied on the knowledge that the human visual system uses edge detection techniques in early vision. They tried to understand and model this process, and on the basis of neurophysical studies developed a computational model for edge detection. Van Vliet et al.[22] developed an adaptive edge detection method based upon the detection of zero crossings in the output image of a non-linear Laplacian filter adaptively oriented to the direction of the local gradient. Moron[23] presented a gradient-determined gray level morphological opening procedure for edge enhancement. Saint-Marc et al.[23] proposed a non-linear filtering method for discontinuity-preserving smoothing; their methods were able to achieve edge sharpening after a few iterations. However, as the method was not primarily designed for sharpening the image, the enhancement achieved was not very prominent.

In this paper we present a modified formula for computing image edge profile acutance (IEPA): the variable-step differences across the ROI boundary as used by Rangayyan and Elkadiki[1] is replaced by a regular difference measure which closely approximates the gradient. We also propose image sharpening operators which are designed on the basis of acutance. As acutance is correlated with image sharpness (Olabarriaga and Rangayyan[25]), one possible approach to image enhancement is to apply enhancement techniques in such a way as to increase the acutance of the ROI. Then, we may expect the perceived sharpness of the ROI to be increased as a result. To achieve this, we investigate the use of one-dimensional operators applied to pixels along the normal at each boundary pixel of the ROI.

The paper is presented in six sections. Section 2 summarizes the previous work on IEPA. The modified formula of acutance will be presented in section 3. Section 4 contains the algorithm for image sharpening. Section 5 presents results of application of the proposed algorithms to test images. The final section draws conclusions and identifies areas in which research effort will be directed in the future.

2. Image Edge Profile Acutance

Rangayyan and Elkadiki[1] proposed a measure of mean-squared gradient computed across and around the contour of an ROI and called it "a region-based measure of image edge profile acutance" or IEPA. They used a region growing method (Morrow et al.[13]) for finding the boundary of the region. The method starts with a seed pixel within the ROI. The region is then grown by aggregating 4-connected pixels which meet a pre-specified tolerance about the seed pixel's gray level, defined as

$$p(k, l) - p(i, j)| \leq t, \tag{2}$$

where $p(i, j)$ is the gray level of the seed pixel and $p(k, l)$ is the gray level at a connected pixel (k, l). The region growing process stops when no 4-connected pixel within the specified gray level tolerance can be found. When the region growing process is completed, the outermost layer of pixels of the region gives the region's external boundary.

Once the boundary is identified, the next task is to find the normals at all positions on the boundary. Rangayyan and Elkadiki[1] suggested consideration of three boundary pixels at a time – the current, next, and previous – to find the normal to the boundary at the current pixel. The algorithm selects a set of nine pixels that approximate the normal at each pixel on the boundary by comparing the relative positions of the three boundary pixels selected.

A new method to determine the normals has been suggested by El-Faramawy et al.[17] Instead of taking only three pixels on the boundary at a time to approximate the normals, they fitted a polygon to the ROI boundary, with the number of sides being dependent upon the ROI shape complexity. A linear equation is then available for each of the sides of the polygon, from which the equation for the normal to each side can be found easily. Using the equations of the normals, the pixels along the normals at each boundary pixel can be obtained. The details of the polygonal approximation method are provided in a paper by Ventura and Chen[26].

In their original work, Rangayyan and Elkadiki[1] used four foreground pixels inside the region and four background pixels outside the region to define the normal. In the modified version proposed by El-Faramawy et al.[17], the number of pixels taken along each normal is variable, taking into consideration edge thickness and the available number of normal pixels. The edge pixel itself is not used in the computation. The following equation is then used to calculate the gradient at the boundary point under consideration (indexed j):

$$\overline{m}(j) = \frac{1}{N} \sum_{i=1}^{N} \frac{f(i) - b(i)}{2i}, \tag{3}$$

where N is the number of pixels taken along the normal, and $f(i)$ and $b(i)$ are the foreground and background pixels, respectively (see figure 1 for details on the index i).

The procedure is repeated at all edge pixels (i.e. all pixels on the boundary of the ROI). After all the normal derivatives are calculated, the root mean squared (RMS) gradient is calculated over all pixels on the ROI boundary. The RMS value is then normalized by the maximum possible RMS derivative. The expression for IEPA is given by

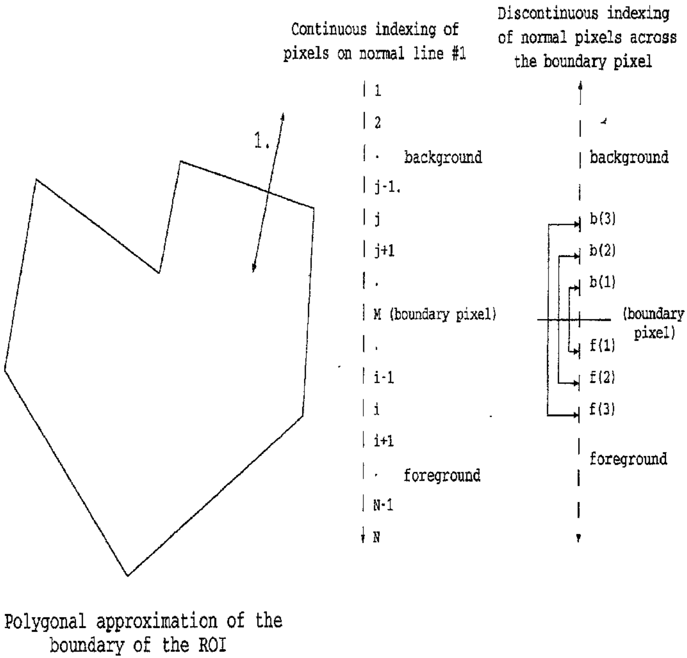

FIG. 1. Indexing of normal pixels inside and outside an ROI.

$$\overline{A} = \frac{1}{d_{\max}}\left[\frac{1}{B}\sum_{j=1}^{B}\overline{m}^2(j)\right]^{\frac{1}{2}}, \tag{4}$$

where $\overline{A}$ is the IEPA, $\overline{m}(j)$ is the averaged derivative at a particular boundary pixel j, B is the number of boundary pixels, and d_{max} is the maximum possible averaged derivative. In the original paper by Rangayyan and Elkadiki[1], d_{max} was calculated to be 132.8125, assuming 8-bit digitization. In the modification suggested by El-Faramawy et al.[17], the value of d_{max} varies, depending upon the number of points taken along each normal. Acutance is a dimensionless quantity.

Olabarriaga and Rangayyan[25] explored the effectiveness of the IEPA measure in analyzing relative sharpness of different images affected by blur and noise. They obtained the subjective ranking of a set of test images and compared the results with the ranking according to the acutance values of the images. They found that trends of IEPA agree well with subjective ranking of sharpness of an ROI.

3. Modified Algorithm for Image Edge Profile Acutance

In this paper, a modification to the formula for computing the gradient across the edge pixel is suggested. The computation of acutance from the gradients is also modified. The gradient is computed continuously instead of being computed using differences between corresponding pixels across the edge[1,17].

For an image with digitized, finite pixels, a continuous derivative operation cannot be performed in the true sense: the normalized difference value between adjacent pixels can be calculated only as an approximation to the continuous derivative. The difference is normalized in order to take into account the varying distance between two adjacent pixels. In an 8-connected neighborhood, the pixels at a corner are $\sqrt{2}$ distance units apart from the central pixel under consideration; the corresponding distance to the other four neighboring pixels is one unit. The gradient or derivative at the pixel i is computed as

$$d_i = \frac{n(i) - n(i+1)}{dist_i}, \tag{5}$$

where d_i is the derivative at the i'th pixel, and $n(i)$, $i = 1, 2, \ldots, N$, are the foreground and background pixels along the normal indexed successively (see figure 1). $dist_i$ is the distance between the i'th and $(i+1)$'th pixel, which is either 1 or $\sqrt{2}$ as discussed earlier.

After the gradient is calculated, the local acutance at the j'th boundary pixel is computed as

$$A_j = \left|\frac{1}{n(1) - n(N)}\right| \sum_{i=1}^{N-1} d_i^2, \tag{6}$$

where $n(N)$ and $n(1)$ are the pixel values of the N'th and the first pixel along the normal. The edge pixel is used in the computation, contrary to the previous methods[1,17].

The local acutance value is then normalized by the maximum possible acutance at point j, which is

$$A_{\max_j} = \sum_{i=1}^{N-1} 255^2. \tag{7}$$

A_j in equation (6) will be maximum when the numerator is maximum and the denominator is minimum. The numerator will be maximum when each pair of pixels has unit distance and a pixel value difference of 255 (assuming 8-bit digitization). We have assumed that the background of an object does not include another object, and that the denominator can have a minimum value of 1.

Equations (6) and (7) are applied at all edge pixels. After all normalized local acutance values have been calculated, the final acutance is computed by averaging the normalized local acutance values over all pixels on the boundary as

$$A = \frac{1}{B}\left[\sum_{j=1}^{B} \frac{A_j}{A_{\max_j}}\right], \tag{8}$$

where A is the final acutance value and B is the number of pixels on the boundary. Acutance A above is a dimensionless quantity similar to the one defined by Higgins and Jones[2].

The most important difference between the proposed algorithm and the previous algorithms[1,17] is in the definition of the gradient. According to the original definition given by Higgins and Jones[2], acutance or edge sharpness is related to the mean-squared gradient of the edge. The algorithms of Rangayyan and Elkadiki[1] and El-Faramawy et al.[17] approximated the gradient by taking normalized differences across the edge with the inherent assumption that the edge is of only 1-pixel width. In real situations one can identify only a region containing the edge instead of finding the exact edge-pixel. Therefore it is more appropriate to take the difference between successive pixels, which is independent of the knowledge of the exact edge pixel.

Secondly, the previous method of taking the differences between corresponding pixels across the edge is dependent on the knowledge of the exact position of the edge pixels. The exact position of edge pixels cannot be determined for most natural images. Approximating the derivative by taking differences across the edge pixel is arbitrary as well. Theoretically, the gradient at any point of a discrete function is approximated by the normalized difference with respect to the previous point. The edge function of a digital image is a discrete function and hence the gradient of the edge should be calculated using the method described in the proposed algorithm. Therefore the proposed algorithm can be taken as the formal definition of acutance for digital images as it agrees with the original definition of acutance given by Higgins and Jones[2].

4. Image Enhancement Based on Acutance

As acutance is related to the sharpness of the image, the image could be enhanced by using operators which increase the acutance of the ROI. Acutance is calculated using pixels along the normal at each boundary point. The proposed enhancement algorithm applies one-dimensional operators on the normal pixels. The operators are derived using the following principle.

When an image is blurred, the gradient of the edge is decreased, which is confirmed by a reduced acutance value. The gradient of the edge becomes lower as the differences between the values of pixels belonging to the foreground (object) and the background become smaller. This implies that the values of the background (or the foreground) pixels get farther from the average background (or the average foreground) value.

The gradient value of a blurred edge may be increased by processing the edge pixels so that they become closer to the foreground (or the background) value. There are two difficulties associated with this approach. The first difficulty lies in identifying the edge pixels; in real images, the edge pixels are not defined well. The second difficulty is that a priori knowledge of the image is not available in most cases, and hence it may not be possible to ascertain the amount by which the pixel values need to be changed. The proposed algorithm reduces the gray level differences between the edge pixels and the foreground (or the background) pixels without assuming any prior knowledge of the edge pixels or their values before blurring, as follows.

The normal pixels at each boundary point are found by the method proposed by El-Faramawy et al.[17] and summarized in section 2. The enhancement algorithm starts with the farthest normal pixel in the background and proceeds towards the ROI boundary along the normal, while applying an operator such that the processed normal pixel values get closer to the background value. The one-dimensional operator used is

$$n(j) = 2n(j-1) - n(j+1), j = 2, 3, \ldots, M, \tag{9}$$

where n is the normal pixel array, j is the index of the pixel under consideration, and M is the index of the boundary pixel in the normal array (see figure 1). The operator in equation (9) applies more weight to the pixel closer to the background than to that closer to the boundary. The changed pixel value is successively used for processing subsequent pixels.

The operator is applied along the normal pixels at each ROI boundary pixel. Some pixels may be selected for processing more than once. There are two approaches to consider regarding multiple processing of a normal pixel. The first approach is to allow several modifications to the same pixel and then to take the average of the processed values. The second approach is to process each pixel only once by using flags. We observed in our experiments that the second approach provides a better performance than the first.

A problem associated with the operator in equation (9) is that false contours may appear in the processed image. As the operator is a one-dimensional operator, it processes a pixel on the basis of its two neighbors only, instead of the two-dimensional 4- or 8-connected neighborhood. As a result, the value of the processed pixel may change drastically after processing when compared to the unchanged neighborhood, resulting in false contours. To prevent this problem we add a restriction such that the difference between a pixel value before and after processing is less than a threshold value. If the processed pixel value changes by more than the threshold, then the algorithm retains the original value of the pixel and does not mark it as "processed", and the pixel is available for further processing. The value of the threshold is determined by trial and error.

The algorithm compares the relation of the j'th and the $(j-1)$'th pixel before and after processing. If the value of the j'th pixel was less (more) than the value of the $(j-1)$'th pixel before processing but becomes more (less) after processing, then the algorithm retains the original value of the pixel. The pixel is not marked as processed, and is available for further processing.

For processing normal pixels belonging to the foreground, the algorithm is the same as for processing the background pixels; however, the sense of differentiation along of the normal array is in the opposite direction (see figure 1). The operator used for processing the foreground pixels is

$$n(j) = 2n(j+1) - n(j-1), j = N-1, N-2, \ldots, M+1, \tag{10}$$

where N is the number of pixels in the normal array and M is the boundary pixel index.

The operator in equation (10) applies more weight to the pixel which is closer to the foreground or ROI center than to the other pixel used in the differentiation operator. For maintaining the mutual relationship between neighboring pixels, the algorithm compares the j'th pixel with the $(j+1)$'th pixel.

5. Results

5.1. *Modified algorithm for acutance*

The modified algorithm was evaluated on the two test images used by Rangayyan and Elkadiki[1]. The acutance computed by the proposed modified algorithm lies in a different range, but follows the same trend for different versions of the test images as exhibited by the acutance values obtained by Rangayyan and Elkadiki[1]: Acutance decreases as sharpness decreases (with increased blurring). Histogram equalized images have increased acutance values, with the versions after subtracting Laplacian and histogram equalization operations having larger acutance values than the original and the one after histogram equalization alone. The modified method, however, is more sensitive to noise, and acutance increases slightly with the addition of noise.

The absolute value of the acutance computed by the proposed method is small (acutance values for the test images used in the present study will be discussed in the next section), which may be due to the over-restrictive nature of the maximum value used to normalize the acutance. The algorithm takes the maximum pixel value difference between two adjacent pixels as 255 (assuming 8-bit digitization). However, the pixel value difference between two adjacent pixels, both belonging to the background (or the foreground) cannot be 255 because of the way the pixels are aggregated to form objects. The maximum value of acutance, which occurs for a bi-level ROI, is less than 1.

5.2. *Image enhancement based on acutance*

The image enhancement algorithm was tested on two synthesized images. The first image is a 256×256 synthesized image containing a uniform square of size 90×90 and gray level 128 on a uniform background of gray level 255 (figure 2a). The second image is a 512×512 bi-level image with various objects in the form of rectangles, circles, and triangles. The gray level value of the objects was 0, with the background being a constant of 255. The various objects were allowed to intersect, with the gray level of the intersection being 0. Each region is thus uniform (i.e. the second test image is piece-wise constant). Figure 3a shows the second test image. Both

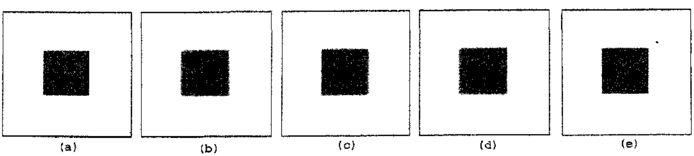

FIG 2. Original, blurred, and sharpened versions of the first test image (a) original, (b) blurred, (c) enhanced by subtracting Laplacian, (d) enhanced by unsharp masking, (e) enhanced by the proposed method.

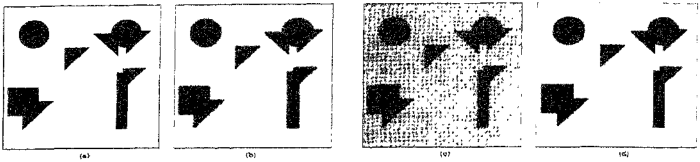

FIG. 3. Original, blurred, and sharpened versions of the second test image. (a) original, (b) blurred, (c) enhanced by subtracting Laplacian, (d) enhanced by the proposed method

the images were blurred once by applying a 7×7 mean filter; the corresponding images are shown in figures 2b and 3b, respectively.

The first test image was sharpened by subtracting Laplacian, unsharp masking, and the proposed method. The pixel values in the processed images were linearly mapped to the range 0-255 for display. The conventional spatial domain sharpening operators (the subtracting Laplacian operator and the unsharp masking operator) did not produce any significant improvement in the images; further, they produced noticeable edge artifacts in the processed images. The different images in figure 2 illustrate the enhancement achieved by the proposed method and also by the conventional sharpening operators. Edge profiles for the original, blurred, and the processed images are shown in figure 4. The profiles confirm that the proposed method sharpens the image more than the conventional methods, and further that the edge artifact produced by the 3×3 operators is absent in the result of the proposed method.

The acutance values of the original, blurred, and processed versions of the square image are listed in Table I. From the table it can be observed that the subtracting Laplacian operator increases the acutance value of the blurred image. The increase in acutance value due to the unsharp masking operator is less than that produced by the subtracting Laplacian operator. The proposed enhancement algorithm increases the acutance value by the largest extent.

The second test image was sharpened by applying the subtracting Laplacian operator and our proposed method to each of the five objects in the image. The subtracting Laplacian operator produced edge artifacts and did not produce good enhancement. On the other hand the image was sharpened considerably by the proposed method. Figure 3 shows the different versions of the second test image, and figure 5 shows representative edge profiles of the images in figure

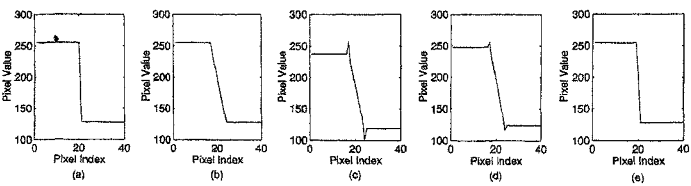

FIG. 4. Edge profiles of the images in figure 2.

Table I
Acutance values for the different versions of the synthesized square image in figure 2.

Image	Acutance times 100
Original	0.4333
Blurred	0.1628
Enhanced by subtracting Laplacian	0.2345
Enhanced by unsharp masking	0.1853
Enhanced by the proposed method	*0.3094*

3. The profiles show that the proposed method increases sharpness more than the subtracting Laplacian operator. However, figure 3 shows that some artifacts appear at the corners of the objects. Note also that the circular region has been sharpened to a lesser extent than the other regions.

The acutance values of the five regions in the four images in figure 3 are listed in Table II. The blurred regions have much less acutance values compared to their original values. The acutance values are slightly increased for the subtracting Laplacian results. The proposed method increases the acutance values by a larger factor than the subtracting Laplacian.

6. Discussion and Conclusion

We have proposed a modified method for computing the acutance of an ROI; the proposed algorithm is an extension of the work by Rangayyan and Elkadiki[1] and El-Faramawy et al.[17] The method uses the conventional difference operator instead of a variable-step difference operator.

We have also suggested a method of increasing the sharpness of an image on the basis of its acutance property. The method has shown considerably better performance than conventional spatial operators (such as 3×3 subtracting Laplacian and unsharp masking operators) and frequency domain sharpening operators (e.g. Butterworth high-emphasis filter, not shown here) when applied to test images.

Initial tests of the methods, as reported here, have been limited to bi-level, synthesized images. Thresholding the blurred image could be an effective way to remove the effects of blurring in bi-level images. However, while thresholding restores the sharpness of the image, edges are often displaced in the enhanced image. The proposed enhancement algorithm maintains edges in almost the same position as in the original image. Restoration filters such as the Wiener filter[18] require exact knowledge of the blurring function. The proposed method, on the other hand, works without any a priori knowledge of the blurring function or the original image.

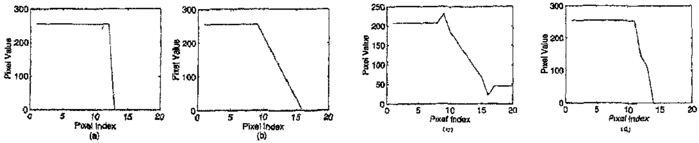

FIG. 5. Edge profiles of the images in figure 3.

Table II
Acutance values for the different versions of the synthesized test image in figure 3

Region	Acutance times 100			
	Original image	Blurred image	Sharpened by subtracting Laplacian	Sharpened by the proposed method
1	0.5864	0.3438	0.3979	0.4599
2	0.5575	0.2221	0.2300	0.3579
3	0.7119	0.3227	0.4513	0.5003
4	0.7469	0.2834	0 3396	0.4637
5	0.6970	0.0428	0.3714	0.4663

The proposed method has some minor limitations as mentioned earlier. The problem of corner artifacts is due to difficulties in finding the normal pixels at corners. The boundary of a circular ROI cannot be very well approximated by a finite number of linear segments; thus the degree of enhancement is less for a circular ROI. These limitations will be addressed in our future work.

The algorithm concentrates on improving edge sharpness only. Currently we are exploring the possibilities of enhancing or sharpening the interior details of regions with gray level variations by suitably modifying the algorithm. We intend to test the effectiveness of the algorithm in enhancing natural and medical images.

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